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Li

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- [54] **SELF-OPTIMIZING METHOD AND MACHINE**
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[*] **Notice:** The portion of the term of this patent subsequent to Dec. 1, 2004 has been disclaimed.

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Related U.S. Application Data

- [63] Continuation-in-part of Ser. No. 652,494, Sep. 19, 1984, Pat. No. 4,710,864.
[51] **Int. Cl.⁴** G05B 13/02
[52] **U.S. Cl.** 364/148; 364/151; 364/152
[58] **Field of Search** 364/148, 149, 151, 152, 364/513

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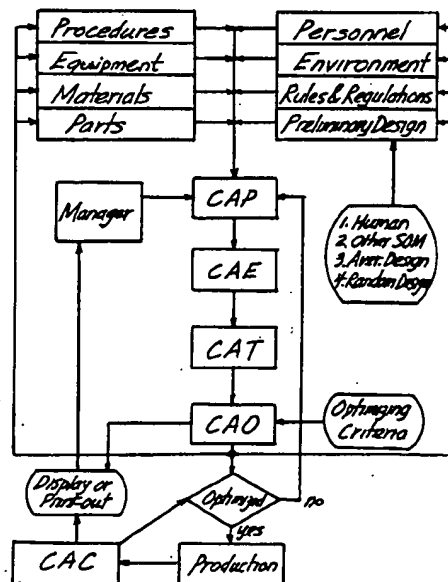
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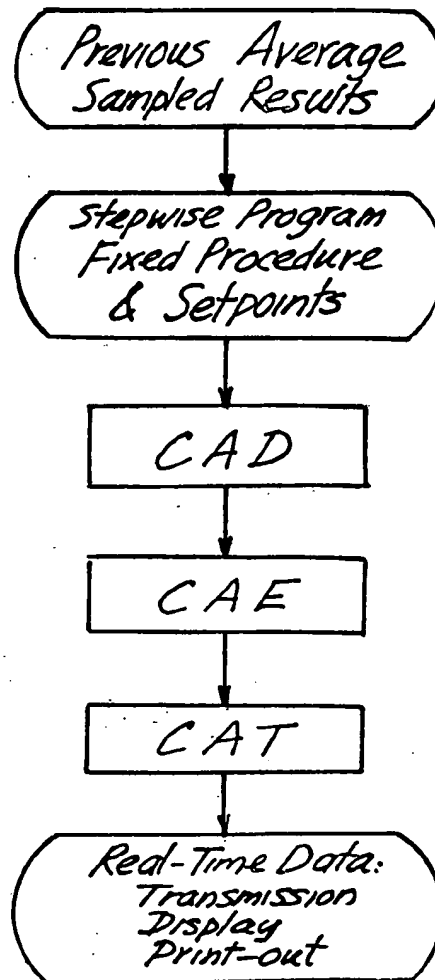
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[57] **ABSTRACT**

A method for self-optimizing an object relative to a specific criterion or activity in response to variations on a prescribed number *m* of variables, comprising: computer-planning a set of *n* statistically designed, fractionally factorial tests for testing the *m* variables; performing the *n* tests on the very object in actual operation; determining from the *n* tests the combination of the *m* variables which optimizes the specific criterion or activity during the actual operation; setting the conditions of the *m* variables at the thus-determined optimal combination before the combination significantly changes; repeating or recycling the self-planning, performing, determining, and setting steps; and during each optimizing cycle employing the optimal combination as the experimental point in the immediately following recycle. A machine which self-optimizes according to this method is also disclosed.

31 Claims, 3 Drawing Sheets



Prior Art*Fig. 1*

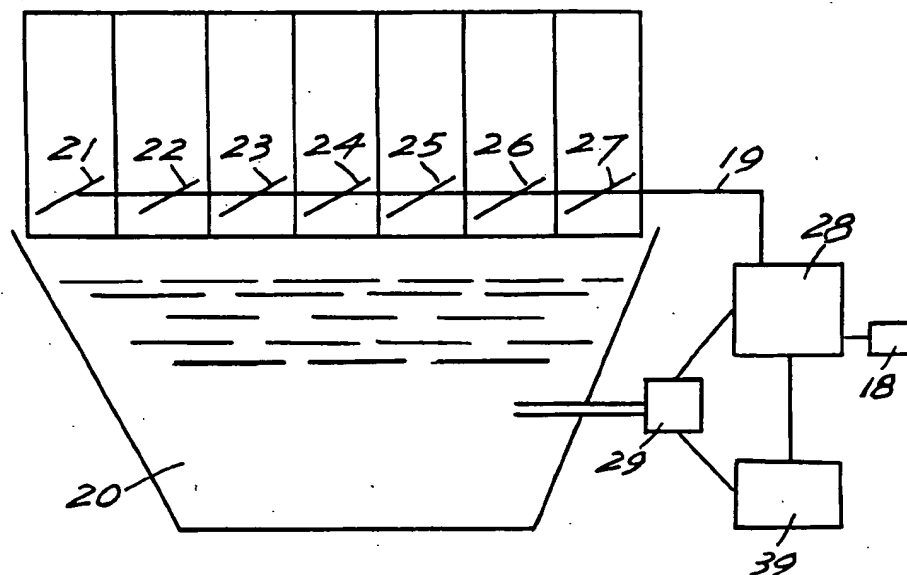


Fig. 2

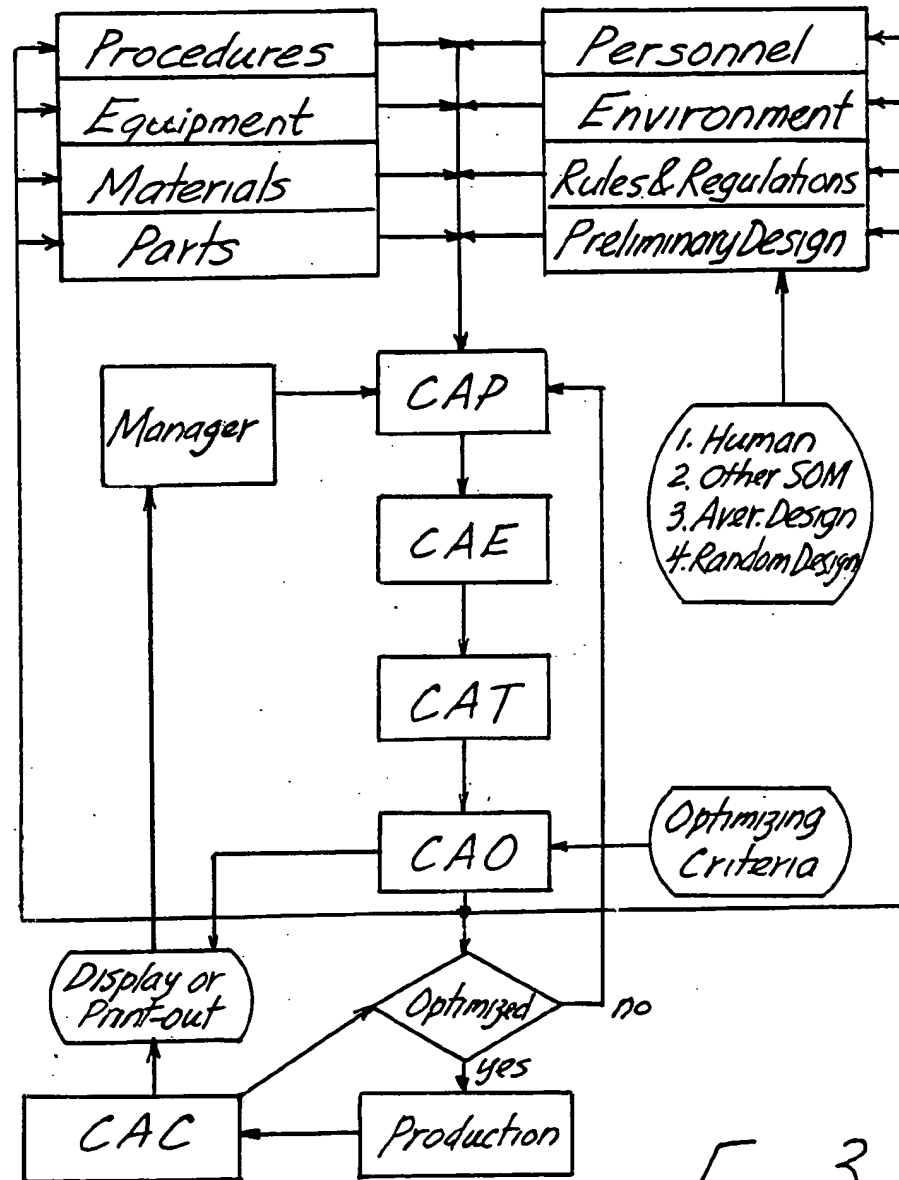


Fig. 3

SELF-OPTIMIZING METHOD AND MACHINE

CROSS-REFERENCE

This is a continuation-in-part of my pending U.S. application Ser. No. 06/652,494, filed Sep. 19, 1984, now U.S. Pat. No. 4,710,864. I hereby incorporate by reference this U.S. patent, as well as its related U.S. Pat. Nos. 4,472,770 and 4,368,509, as well as the related application Ser. No. 69,297, now abandoned.

BACKGROUND

1. Field:

The invention relates to self-optimizing method and machine; and more particularly to multivariable, real-time self-optimizing method and machine, for operation in practical or nonideal conditions involving multiple errors due to defective knowledge bases, miscalibrated sensors, imperfect equipment, and statistical fluctuations.

2. Prior Art:

Computer-controlled, automation systems are widely used. All these systems are extremely powerful. With their uses, consistency is generally achieved together with the usually, but not necessarily always, associated improved profits, productivity, and product or service qualities (P3Q).

Further, by transferring to machines human intelligence, rather than skill, these systems have ushered us into this Second Industrial Revolution.

But human intelligence or knowledge bases only document averaged previous test results on old samples with equipment, materials, parts, procedures, or environment different from the present or future. Inherent are errors due to the various samplings, assumptions, or extrapolations, and repeated human interactions. These knowledge bases are often incomplete, inaccurate, biased, erroneous, out-of-date, and too generalized for uses in a particular automation task with a specific combination of equipment, procedures, materials, parts, and environment.

Detailed knowledge bases on modern technologies are particularly lacking. Even many old technologies are not fully mastered or understood. Each of these technologies involves many processing steps often with unknown chemical, mechanical, electromagnetic, aerodynamic, fluidic, and other phenomena on the subatomic, atomic, microscopic, macroscopic, or other levels. Even the controlling variables in each phenomenon are often not completely known, and certainly have not been comprehensively studied. In fact, much R&D remains to be done in every field. Yet time is running very short in this highly competitive world. A new R&D method must, therefore, be developed.

For example, system dynamics of modern processes and equipment are generally ill-defined. Chemical and metallurgical reactions are often uncertain. The mechanism of catalyst is not completely known. Crystal growth is still an art. After millions of controlled welding experiments, the critical welding variables cannot yet be even identified among the very many possible. In the case of the new high temperature ceramic superconductors, the samples are still hard to make, shape, purify, reproduce, isolate, stabilize, confirm, or even determine compositions.

Without reliable knowledge bases, the usual automation specialist would be at a loss in selecting the few among many manufacturing or servicing phenomena or

variables to be controlled, in formulating the system dynamics models, in setting up the control equations, in determining the control constants, and in specifying the setpoints for the control variables.

The fragile and unreliable knowledge bases often give only partial or invalid system dynamics models, oversimplified control equations, and inexact or misleading control constants. In addition, all the setpoints are too arbitrary and round-numbered (e.g., 800 C and not 796.768 C, 3 feet per minute, 20 gallons) to be possibly optimal statistically. The chance of these variables or setpoints being optimal at any time, not to say instantaneously, is zero. Further, the optimal setpoints cannot be constant, as is assumed in present automation systems, but change with variations in time, equipment, procedures, materials, parts, and environment.

These conventional automation systems are also not smart and must be spoon-fed at every step via computer programs or master-slave instructions. They are not totally integrated or automated, and require constant human guidance, reviews, analyses, interactions, and supervision.

Due to this repeated human involvement, the conventional automation systems not only are greatly slowed down, but inevitably inherit the many defects of the inconsistent and imperfect human test planners, samplers, testers, data collectors and analyzers, communicators, and technicians. Humans are million times slower and less reliable than microprocessors in, e.g., memory recalling or storing, information inputting or outputting, data analyzing, communicating, and commanding or actuating.

In addition, usually these present systems merely passively adapt, adjust, correct, control, or regulate, in response to variations in the environment or a few control variables. Dealing with more than several interacting variables results in extremely large number of tests to be made; and in massive amount of data to be collected, conditioned, stored, and quickly or instantly analyzed. This is often impractical or impossible, because of the well-known problems of "combinatorial explosion" and "computer intractability," as has been described in the '864 patent.

Yet, modern technologies invariably involve many unpredictable, interacting, and rapidly changing control variables in such categories as: raw materials vendors, batches, lots, and conditions; compositioning; processing equipment; procedures in each of the many steps; and environment. Many phenomena are transient but highly nonreproducible yet unknown and critical.

Artificial intelligence technologies, particularly, the expert systems, have been developed and increasingly used in various fields. But again the knowledge bases are often inadequate or deficient, particularly on developing technologies. The present expert systems are also costly, inflexible, qualitative, and often inaccurate and out-of-date particularly for complicated yet rapidly improving modern technologies. In addition, they too cannot handle the inherently large numbers of interacting variables.

Reliable and relevant knowledge is scarce and very costly. Up to now, the main bottleneck in the development of expert systems has been the acquiring of the knowledge in computer-usable form. Human knowledge often not only is fragile, costly, unreliable, but difficult to be translated for uses by machines. Codify-

ing an expert's skill has always been a long and labor-intensive process.

Hence, experts conclude that machine learning is the key to the future of automation in general and expert systems in particular. The valuable knowledge must be manufactured, in bulk. So far, however, no such machines exist.

Present automation systems also invariably involve various hidden errors of samplings, assumptions, extrapolations, scaling-ups, and statistical fluctuations of uncertain magnitudes. These systems are also at the mercy of other errors due to, e.g., miscalibrated sensors, imperfect actuators, drifting equipment, and partially damaged components. Any one of these errors can easily lead to unexpected inconsistencies and nonuniformities in, e.g., manufacturing or servicing results.

Accordingly, an object of the present invention is to provide improved self-optimizing machine and method;

A further object of the invention is to provide real-time self-optimizing machine and method capable of handling tens, hundreds, thousands, or more variables with no or minimum human guidance;

Another object of this invention is to provide close-looped, self-optimizing machine or method which can optimize practically continuously and instantly;

A broad object of the invention is to provide self-optimizing machine or method based on totally self-planned and controlled tests, performed on the very particular machine or method itself without relying on many assumptions, invalid scaling-up laws, and extrapolations from sampled test results obtained on other similar machines or methods; and with practically instant data analyses for timely optimization results;

Another object of the invention is to self-optimize machine or method in practical or nonideal conditions by tolerating, neutralizing, or suppressing the effect of errors due to defective knowledge bases, miscalibrated sensors, imperfect actuators, drifting equipment, damaged components, and statistical fluctuations;

A further object of the invention is to provide self-optimizing machine or method which operates even with deficient and minimal or practically zero knowledge bases, rapidly generates its own new knowledge bases through automatic R&D, and immediately and continuously replaces these new knowledge bases with still newer and more accurate or refined knowledge bases for continuously optimal results;

An additional object of the invention is to provide self-optimizing machine and method which actively computes, and automatically sets at, the instantaneous optimum combinations of the many relevant variables in various categories, with instant feed-back to supply data for immediate replanning, retesting, and reoptimizing, all without human intervention;

Another object of the invention is manufacture, in bulk, reliable knowledge bases for the instant development of relevant expert systems.

Further objects and advantages of my invention will appear as the specification proceeds.

SUMMARY

To these ends, the present invention provides a method for real-time self-optimizing, with instant or substantially continuous, closed-loop feed-back control but without human guidance, intervention, and interaction, by automatically, instantly, repeatedly, and preferably continuously: planning efficient, statistical design matrix of n tests on m variables with n being less than 2

to the $(m-4)$ th. power ($\frac{1}{8}$ replicated, or one eighth of the required test number for the complete, m -variable factorial experiment), adjusting the conditions of the m variables according to the design matrix; performing the necessary tests; collecting and recording the n sets of data on the critical performances to be optimized; analyzing the collected data to determine the functional relationships between the m variables and the critical performances or the instantaneous optimal variable combinations; setting the m variables to the thus-computed optimal combinations before these combinations change; and feeding back information on the status of optimization to achieve closed-loop feed-back control. A machine operating on the basis of this method is also disclosed.

BRIEF DESCRIPTION

The invention and its further objects and features will be more clearly understood from the following description taken in conjunction with the drawings in which:

FIG. 1 shows the flowchart of present automation systems;

FIG. 2 shows a self-optimizing furnace for making special iron-base alloys; and

FIG. 3 shows the flowchart of my self-optimizing machine and method.

DETAILED DESCRIPTION

The method and machines of the invention are of general applicability for self-optimizing many and various automation systems and processes, in real time and with lightening speeds in the dealing of many, many variables, which normally require thousands, millions, billions, or more computational steps.

FIG. 1 shows the flowchart for the present automation systems. Note that these systems totally depend on the imperfect and error-prone human knowledge bases from averaged previous sampled results. Also, there are no mechanisms to eliminate, suppress, or even detect errors from any sources. Hence, errors in, errors out.

Thus, a fundamental flaw in present automation systems is the assumption that there exist human experts who know exactly and accurately everything: the exact number and type of important variables and their interactions, system dynamics models, detailed solutions of the intricately coupled control equations, exact control constants, and optimal setpoints. In reality, this is far from the truth.

As a result, wrong models based on incomplete or imperfect understanding often must be used, with misleading, dangerous, or disastrous results. Classical examples include the Space Shuttle disaster, Chernoby reactor failure, the downed Korean airline and Hitler's Russian invasion. In the last example, Hitler gathered at least all the German weather experts to help program the step-by-step operational procedures for his human and mechanical robots, based on collected massive, accurate, and scientific, but misleading previous sampled weather data, with disastrous results to his whole army on the Eastern Front.

FIG. 2 of this application, and FIG. 1 of the '864 and '770 patents as well as FIG. 2 of the '509 patent, all show a machine 20 in the form of a furnace to make special iron-base alloys. The furnace self-optimizes, in real time, relative to a specific performance, e.g., hot tensile strength of the resultant alloy produced on the furnace, in response to variations in a fixed number m of variables. For ease of illustration, m is only 7 and all

these 7 variables are 7 alloying elements. The composition of these seven alloying elements can be changed continuously and without steps. These variables are continuous variables. This machine or furnace has a built-in microprocessor 28 which first self-plans a statistical design matrix of operating or alloying procedures or conditions for the automatic R&D according to, e.g., the method and computer program given in the '509 patent. Specifically, 8 tests or alloying compositions are planned, or only a one-sixteenth fraction of the 128 as required by the complete 7-variable factorial experiment. Thus, while a complete seven-variable (at two levels each) experiment requires the making of 2 to the seventh power, i.e., 128, tests, this self-planned fractional factorial experiment makes only 8 tests, or one-sixteenth (8/128) of the required number of 128 (=2⁷). Technically, this is called a one-sixteenth fractional factorial experiment. The microprocessor then directs, through the transmission line 19, the seven actuators or alloying elements feeders 21-27 to feed successively according to the design matrix. The furnace then sequentially makes the 8 (=n) successive tests or melts of iron-base alloys, which are sampled by sampler 29 and tested on tester 39. The test results on the critical product performance, i.e., hot tensile strength of the resultant alloys, are transmitted to the microprocessor 28 (with attached memory 18) for data analyses to compute, as shown in the '509 patent, the desired functional relationships including: effects of the various variables or alloying elements, the instantaneous optimum combination of the variables, and/or the steepest ascent path since the composition variables are continuous variables. The microprocessor 28 then redirects the feeders 21-27 to provide the optimum combination of the alloying elements into the molten iron melt in the furnace 20 for optimized alloy manufacture. Periodically, i.e., every hour, minute, or second, the planning, sampling, testing, data analyzing, and feeders actuating and setting are repeated so that the furnace conditions are always maintained optimal. Other details of the principle, operation, and results of the self-optimizing method and machine are provided in my patents, applications, and referenced U.S. patents elsewhere incorporated.

Minor modification of the above self-optimizing machine yields a drug-searching or administering machine continuously self-optimized to dispense the instantly optimum combinations of drugs such as chemicals, plants, animal tissues, bacteria, genetic or biochemical materials, . . . through the feeders, 21-27 into a drug-preparing or feeding device. Such a device, in the form of a hypodermic needle, mouth-feeder, or implanted feeder, will dispense the optimum combination of drugs either periodically or continuously. The tester 29 is used here to test the medical conditions of the human, animal, or plant patient as to, for example vital functions of the organs; chemistry of the blood, urine, and other liquids; or other data or performances to be optimized. Such a self-optimizing machine can also feed food, nutrients, vitamins, or even educational or training materials to plants, bacteria, animals, or humans with optimal equipment, procedures, and environment to achieve self-optimized physical or mental growth conditions of the object at all times.

To search or screen among thousands or millions of drugs for a few that can cure a critical disease such as cancer or Aids, my sequential screening technique given in the Journal of American Statistical Association, Vol. 57, pp. 455-477, 1962, may be used, as has

been disclosed in my '509 patent referred above. In this way, optimum combinations of drugs can be systematically researched and found, to be delivered to the patient in real time.

The flowchart of the new system is shown in FIG. 3. Multiple sensors sense numerical data (having much higher information content than yes-no question-answers in present expert systems) on the system and product or service qualities and also on the many interacting, independent or controlling variables in various categories such as procedures, equipment, materials, parts, and environment. With this information, the microprocessor (e.g., 28 in FIG. 2) continuously or instantly and automatically plans (CAP or AIP) efficient statistical experiments around an experimental point in the m-dimensional experimental region according to, e.g., designs of the highly fractional replicate type as shown in the '509 patent and the Worksheet paper given in Chemical Engineering, Apr. 2, 1958. Without interrupting the system in the performance of its assigned tasks, i.e., automatic manufacturing or servicing, the computer-planned designed experiments are continuously and automatically executed (CAE) to achieve successively the required combinations of variable settings (or elemental compositions) through, e.g., the actuators 21-27 in FIG. 2 for continuous and automatic testing (CAT). Test results on the dependent or controlled variables (e.g., hot tensile strength) including the system and product/service performance data are continuously, automatically, and instantly analyzed and optimized or maximized (CAO or AIO), based on specified or computed optimizing criteria, such as the various system and task goals in proper weighing indices for a particular situation (e.g., only maximum hot strength in the example of FIG. 2). More specifically, the instantaneous optimal variables combinations (or elemental compositions) are continuously determined and, through actuators, set and reset.

The '509 patent discloses the specific software to compute the "effects" or partial derivatives of the m variables on the m-dimensional response surface. These derivatives provide the basis for climbing the hot-strength response mountain along the steepest ascent path, to reach the instantaneous optimum point in the m-dimensional experimental region via the method fully described in the prior art, particularly the '509 patent and my Worksheet paper referred to therein. Alternately, the microprocessor can instantly rank the n test results to determine the optimum performance on test k which, by definition, has the instantaneous optimal variables combination. The next self-optimizing cycle, if needed, will then involve automatic R&D around this new experimental point represented by test k.

The '509 patent also teaches a method to determine the interactions or combined effects, couple(i,j), of any two of the m variables i and j. These interactions are generally neglected, particularly when the units of change of the m variables are small and linear effects predominate.

All the sensed system and product or service performance data are then evaluated to see if the system is optimized. If not, the above optimizing cycle is repeated. If optimized, operation of the system is continued, with 100% continuous and automatic checking (CAC) or quality control of all the sensed performance data for 100% traceability.

The results of the data analyses in the CAO and CAC steps can be real-time displayed or printed-out on a

word-processor in the form of research papers/reports or operating manuals describing comprehensive statistical experiments; instantaneous, complex system dynamics (e.g.); functional relationships between the control variables and the system and product or service performances; new and realistic specifications on these performances; best system modifications and operating procedures; optimum raw material compositions, vendors, lots, and conditions; best equipment layout; and other rapidly generated, reliable, but low-cost knowledge bases.

Note that such displays or print-outs are not for the raw sensed data, as is usually the case. Rather, they are extremely useful and commercially valuable conclusions from the comprehensive, systematic, relevant, and exactly but automatically executed R&D. Most of such information will be totally new and not obtainable for months or years by teams of specialists because of the combinatorial explosion problems mentioned above.

These knowledge bases are, furthermore, manufactured in great bulk at very low cost, and are instantly machine-codeable so that "expert systems" can be easily generated at a small fraction of the cost and time compared to the conventional approach. The development of expert systems is a well-developed art. See, for example, P. Klahr's book on "Expert Systems: Techniques, Tools, and Applications," published by Addison-Wesley in 1986; and W. B. Genarter's paper entitled: "Expert Systems: Limited but Powerful," in IEEE Spectrum, Aug. 1983.

Each expert system typically has as its components the knowledge base, an inference engine, a knowledge-acquisition module, and explanatory interface.

My self-optimizing machine always has a knowledge-acquisition module to generate in the CAO and CAC steps the required knowledge bases in a particular domain of interest. These knowledge bases are automatically codeable into an inference engine to provide "advices" as its outputs. In the steel-making furnace operation given above, for example, the machine-generated rules may be: "IF hot strength is needed, THEN in the order of decreasing effectiveness one should increase V, Cr, Mo, Nb, and C, but decrease Mn and Ni (See "Effect" column in Example 1 of the Worksheet reference);" "IF maximum percentage effect is needed, THEN one should add V;" and "IF maximum hot strength is needed, THEN use the following best combination of the seven elements: 10.4% Cr, 1.2% Ni, 0.66% Mo, 0.18% V, 0.58% Nb, 0.24% Mn, and 0.80% C," as indicated in line 25, Trial 11 of Example 1. Also, "IF V is 0.18% and Cr is 10.4%, THEN Mo should be 0.66% and Nb 0.24%". These rules can easily be codified and printed out with standard formats requiring merely the filling of the variable names such as Cr, Ni, Mo, . . . and the numerical values such as 10.4, 1.2, 0.66, . . .

Thus, my self-optimizing machine readily and automatically generates these and other similar rules in computer-coded form ready for use in instant machine expert systems. The displays, print-outs, and transmitted data (FIG. 2) provide the "explanatory interface," as in the conventional expert systems.

To fully utilize my self-optimizing machine, however, these "rules" are preferably instantly and automatically implemented through actuators without introducing any delays or errors due to the presence of humans in the loops.

Even probabilistic statements in the rules can be provided, if needed, because the automatic statistical exper-

imentation during each self-optimizing or R&D cycle provides a valid "experimental error," from which confidence limits can be derived. The errors in each estimated effect or interaction, for example, can thus be estimated. See standard textbooks on statistics.

In this way, my self-optimizing machine solves the present main bottleneck in the development of expert systems, i.e., the acquisition of knowledge in computer-usable form; and meets the long and keenly felt need to automate the knowledge generation process.

Thus, the machine-generated information of my invention forms the basis of a new kind of artificial intelligence or knowledge bases. These bases are comprehensive in the number of control variables, the range of these variables, and the scope of the experimental region. These knowledge bases are also relevant, timely, reliable, less error-prone, and possibly instantly available.

Note that the self-optimizing process is performed on the very automation machine or object of interest and in actual operation, with the exact raw materials, parts, procedures, equipment, and environment. In addition, the test data are quickly collected, analyzed, and used on the very machine or object to be optimized during the same actual operation. Hence, the various ever-present and often critical errors of sampling, extrapolation, and scaling-up are minimized or eliminated.

A unique feature of my self-optimizing technology is that the computing time in each self-optimizing or automatic R&D cycle may take only milliseconds or microseconds, as will be shown. Delays due to mass and thermal inertia or diffusion effects, however, generally are much larger than this negligible computing time. These motioning, positioning, heating, cooling, and stabilizing delays primarily determine the duration of each automatic R&D or self-optimizing cycle. Still, with suitable actuators, sensors, and equipment design or layout, the optimizing cycles may indeed be very short. These short or even instant optimizing cycles make the optimizing process not only simple and possible, but in real time and often practically continuous, even for complex, rapidly changing conditions or processes.

Because of the efficient statistical designs and simplified data analyses, the CAP-CAE-CAT-CAO optimizing cycles may each take only a small fraction of a minute or second, if the testing, actuating, and data sensing have minimal delays. As a specific example, dealing with a case involving 127 (=m) variables at two levels each normally would require making $n=2$ to the 127th. = $1.701E38$ conventional tests, and about $N=3 \times n \times n = 2.895E76$ multiplications, or $8.738E43$ years on a nanosecond computer for the data analyses. Using the technique described here and in the '509 patent, it now requires making only 128 ($n=2$ to the 7th. and not 127th.) tests, and $N=n \times \text{logarithm of } n \text{ to the base of } 2 = 128 \times 7 = 896$ additions/subtractions and 128 divisions or 896 shifts to the right, for a total of 1,024 or 1,792 computational steps or 1.02 or 1.79 microseconds, respectively, on the same nanosecond computer. Even on a microsecond computer, the total data analysis time for each self-optimizing cycle with 127 variables is merely 1.02 or 1.79 milliseconds. Since the CAP step also takes about 1 microsecond or millisecond on the nanosecond or microsecond computer, if sensing, actuating, and testing (CAE and CAT) are nearly instantaneous, the entire optimizing cycle or system response time could thus indeed be a fraction of a minute or

second, through milliseconds down to microseconds, or at least sufficiently fast to meet the requirements of practically all modern technologies.

Our new system would thus make many "impossibly complex" optimizing tasks not only possible but practical and possibly in real time.

In operation, the self-optimizing machine first reads the optimizing criteria on the machine and product or service performances with their different weighing indices, and the number of control variables with their allowable ranges. It is then totally up to the new machine, all by itself, to continuously plan, execute, compute, optimize, and implement the instantaneous optimal variable combinations or automatically determined setpoints.

Any preexisting knowledge bases, if available, are used merely in the preliminary design for each variable in the first self-optimizing or automatic R&D cycle only. If no knowledge bases are available, the self-optimizing machine starts the preliminary design for each continuous variable with the average or midpoint of, or even a random number within, the given allowable range. After the first cycle, comprehensive, relevant, timely, and error-free new knowledge bases will be produced. Even these new knowledge bases will, in turn, most likely be immediately replaced by still newer and more accurate or refined knowledge bases with additional self-optimizing cycles. As shown above, each such self-optimizing cycle may be very short if rapid sensing, actuating, and testing are possible.

As a byproduct, the system thus generates, prints out, or transmits to other self-optimizing machines vast quantities of the error-free, constantly updated knowledge bases. These knowledge bases are suitable for human uses for innovations, hypotheses testing, and advance product development. These knowledge bases are also useful for present automation systems, as preliminary designs for other self-optimizing machines, or for the development of instant expert systems as described above.

This transfer of intelligence from machine to humans or to other machines may signal the beginning of the Third Industrial Revolution.

Advantages of the self-optimizing machine are many, particular when compared to present automation systems. The purpose of present automation systems is to control only certain selected variables within specified limits. These limits may or may not be optimal. Even the selected control variables do not always certainly or reliably affect the productivity and product or service cost/qualities. Much, therefore, depends on the reliability of the knowledge bases; the many assumptions, extrapolations, and statistical variations; and equipment conditions, calibrations, and drifts.

On the other hand, my self-optimizing machine optimizes directly the bottom line, i.e., productivity, cost, and product or service qualities. Improper control models or constants, and variable setpoints thus can do no harm. Because of the unique operating flowchart (FIG. 3), many of the deficiencies of present systems are minimized or eliminated. Even the conditions or calibrations of the equipment, particularly the sensors and actuators, have minimal effects on achieving the desired optimization of the bottom line.

When the control variables are sensed with miscalibrated sensors or set with imperfect actuators, for example, the resultant "instantaneous optimal combinations" as sensed with the miscalibrated sensors and set with the

imperfect actuators are still the most relevant, useful, and best for the particular self-optimizing machine at the specific time with the particular environment to achieve the required optimizing criteria or goals. The miscalibrations and imperfections are always exactly self-compensating.

For example, in the conventional system, the specified setpoint may be 500 C to be sensed by a K-type or Chromel-Alumel thermocouple. If, however, the K-type thermocouple is miscalibrated or if a J-type Iron-Constantan thermocouple is misused, the results can be dangerous in present automation systems. However, in my self-optimizing machine, the zero and proportionality constant calibrations of the thermocouple are unimportant. Even a misuse of the thermocouple merely changes the proportionality constant with a proportional change in the apparent "effect," but no reduced efficiency in reaching the optimized bottom line of profits, productivities, and product qualities.

As another example, a present automatic processing system may specify an optimal control temperature of 100° F. Assume a Fahrenheit thermometer is specified for sensing, but a Centigrade thermometer is misused with a zero-point correction off by 32° F. and a proportionality constant off by $(9/5 - 1) = 80\%$. The controlled process will then be out of control. Still, in my self-optimizing machine, the automatic R&D will determine and set at the self-determined, true instantaneous optimal combinations (or setpoints). The response surface will still be climbed in the steepest ascent manner, even though this response surface has been shifted laterally (because of the zero miscorrection) and has a different height scale (because of a changed proportionality constant).

Sensor zero miscalibration of more than 32° F. (or $32/100 = 32\%$ of the optimal set value) and proportionality miscalibration of more than 80% in temperature, pressure, voltages, current, dimensions, velocities, flow rates, . . . can be similarly tolerated. Actuator or other equipment imperfections due to drags, backlashes, damages, and too wide clearances are also tolerable for similar reasons and, in addition, because of the statistical averaging effects between tests of the same or different self-optimizing cycles.

Similarly, equipment drifts are also tolerable if the automatic R&D cycle time (e.g., 1 or 2½ sec) is less than the drift cycle time (e.g., 5 or 10 sec).

Hence, with my self-optimizing machine, achieving the truly meaningful optimizing goals on product or service costs or qualities is no longer a hostage to the quality of the existing knowledge bases, the correctness of the control models or equations, the exactness of the given setpoints, and the conditions of the equipment.

My optimizing machine is thus error and fault-tolerant and flexible. It can handle practically any number of important, possibly important, or interacting variables, on the most reliable microprocessors, without much regard to the computing speed or memory size. Redundancy or parallel processing may, however, be also employed for additional reliability and computer speed, respectively.

The self-optimizing machine is, therefore, smarter; better; smaller; lighter; faster; and more reliable or flexible than present automation systems, yet may save enormously for its employers while mass-producing low-cost but uniformly optimal-quality products or services.

Most importantly, the self-optimizing machine can timely perform the necessary, complicated optimizing

tasks for the modern, complex yet rapidly changing automation tasks that probably no other systems can.

Further, even the minimum number of tests in each R&D cycle still provides virtual statistical replications, and thus yields averaging effects to counteract the statistical fluctuation and chance combination effects due to sampling, actuator backlashes, and equipment conditions. . . . This is partly because the efficient statistical designs are so balanced that the effect of each control variable can be independently evaluated as if the entire experiment were performed just on this one variable with the other variables all kept constant.

My self-optimizing machine parallelly and automatically performs, depending on need, at least a few of the following important operations during each automatic R&D or self-optimizing cycle:

1. Comprehensive and systematic R&D;
2. Optimal manufacturing designs;
3. 100% quality control
4. Procedure or equipment modifications;
5. Materials and parts selections;
6. Use of environmental changes for maximum benefits;
7. Prototype or finished products manufacturing; and
8. Rapid generation of reliable and comprehensive knowledge bases.

Thus, this new machine should be significantly improved over conventional automation systems (FIG. 1). These later systems perform the various tasks listed above sequentially and successively, and even this very slowly, inefficiently, and often unreliably.

It can readily be seen that the self-optimizing method and machine of the invention can be used for many automation systems in various industries including manufacturing, servicing, office, military, farming, medical, and education.

More specifically, the invention is also useful to self-optimize, in real time, the physical or mental growth activities of a living being selected from the group consisting of human, animal, bacteria, and plant. Such activities including: body growth, physical strengthening, sporting, learning various skills such as speaking, singing, reading, memorizing, swimming, foreign language, and other subjects. The flowchart of FIG. 3 is equally applicable in these cases even with the same microprocessor and basic computer programs for the CAP, CAE, CAT, and CAO steps, as described above. The sensors and actuators used, however, are generally different from those used in the self-optimizing furnace of FIG. 2. The specific performance or activity characteristic used as the optimizing criteria will, of course, also vary depending on the activities involved ranging, e.g., from learning speed, comprehension, growth rate, to others, as is well known to the skilled person. The controlled variables also may include growing, training, and educating procedures; training or growing materials (food, books, recorded tapes, . . .); parts; and environment (such as temperature, humidity, noise or music type, intensity and tempo).

As an example, to self-optimize in real time the learning process of a human such as a child, one may, according to the description given above and in the '864 patent. Sequentially cause the human to do the specific learning activity n times in succession while the conditions of the m selected variables are simultaneously changed according to a design matrix. The m variables may relate to the learning equipment, materials, parts, procedures, and environment, while the optimizing

criterion the speed and comprehension of learning, possible directly measured and scored by the microprocessor. Similarly, in a self-optimized growth process for objects such as human, animal, bacteria, or plant, the object is caused to grow in n different ways by suitably actuating the m growth variables according to the design matrix. The specific performance to be optimized here is usually the growth rate, maximum growth, cost per given growth, and environment impact.

The self-optimizing method of the invention is also useful for other financial, business, office, factory, military, educational, and scientific applications. Even many computer softwares can thus be not only automatically but optimally generated, modified, and used. Here, the same flowchart of FIG. 3 is used. The optimizing criteria may be the usual productivities, product or service costs, profits, and reliability or accuracy. The control variables mostly are different procedures, equipment, and software parts. The physical material and environment variables are usually unimportant. The procedural variables may involve the use of different mathematical or physical/chemical models, equations, or formulas; numerical computational techniques such as for finite element analyses, differentiation or integration, interpolation or extrapolation, root-determining, in different softwares. The procedures or parts variables may also involve the finite element grid shape and size; number, location, and contents of the various subroutines; and the location, size, starting and finishing points, and step size of the do loops. The equipment variables are often important because each microprocessor, disk or tape drive, monitor, printer, modem, transmission line, . . . has unique operating characteristics such as speed, memory capacity, reliability, . . . Again, for the self-optimizing machine, the software optimizing task such as software generation or usage, computer simulation, and computer aided design (CAD), engineering (CAE), or training (CAT), . . . is first defined. The optimizing criteria in different weighing indices are next given. The number, type, and allowable range of the variables in different categories are then fed. As shown, this fed information may include the number, type, location, operating characteristics, . . . of the different coprocessors or on-site slave microprocessors, monitors, disk or tape drives, telecommunicating equipment, modems, printers, . . . ; and the number, type, and characteristics of the different subroutines, do loops, or numerical analytical methods; . . . It is then up to the master processor in the self-optimizing machine to continuously and automatically plan (CAP) or automatically and instantly plan (AIP), and direct the various optimizing steps such as CAE, CAT, CAO, and CAC and, in addition, repeat the self-optimizing or automatic R&D cycles as needed. The effect of using a particular equipment, procedure, or software part is then determined, and the interactions of these variables are computed. One or more of optimizing schemes described above are followed. The optimal combination of the variables is determined and set, redetermined and reset, so that the software generation, modification, application, . . . tasks are optimized statically or continuously optimized in dynamic situations. In these software-related tasks, no physical products are manufactured or serviced, yet the results are just as rewarding. These results may be self-optimized CAD, CAE, computer integrated instruction (or training), simulation, battle management, signal or image processing, sensor data fusion, geopolitical assessments, financial data analyses, and stock, option,

and commodity trading strategy generation and execution.

According to the method of the invention given above, I have developed a real-time self-optimizing heating system or machine. This machine has a 64-K, Apple II Plus microcomputer, a Lindberg Type 54032 or 55035 furnace, a Chromel-Alumel thermocouple sensor, and a 25-Ampere Omega solid-state relay as the actuator. A $3\frac{1}{2}$ -bit A to D converter, a special parallel interface board, and some transmission lines complete the hardware. This machine does not work on a fixed, control program based on preconceived heating dynamics model, predetermined control constants, and setpoints, as is usually the case. Rather, its Apple microcomputer plans its own test design matrix according to the technique described above; directs the relay actuator to be on and off at planned temperatures for designed lengths of times according to the design matrix; collects and analyzes the sensed temperature data to determine, with or without the use of the steepest ascent method, the instantaneous, unique combination of the variables which optimizes the machine performance, e.g., minimum temperature fluctuations, absolute temperature deviations from the set temperature, time to reach set temperature, . . . ; and sets the machine accordingly. Even with the large thermal inertia, within minutes of turning on the machine is heated to and controlled within typically a fraction of a degree Centigrade from the set temperature of, e.g., 500 C. The sensitivity on this machine is limited by the A to D converter. Some other real-time self-optimizing machine have also been developed and successfully tested.

In addition, the '509 patent also points out the various relevant prior arts including Hardaway's extreme parameter search control system (U.S. Pat. No. 3,446,430), Russo's combined pattern recognition and linear regression network (Pat. No. 3,576,976), Smith's digital process control (Pat. No. 3,694,636), and Barron control systems (Pat. No. 3,460,096 and 3,519,998) which provide background for the design and use of control systems, system programming, actuators, calculators, timing circuits, A/D or D/A converters, storage memories, sensors, comparators, logic devices, sign detectors, . . . which are often useful in the practice of my invention. I hereby incorporate the listed essential materials of these patents into this application by reference.

The invention is not to be construed as limited to the particular forms disclosed herein, since these are to be regarded as illustrative rather than restrictive.

I claim:

1. A machine for self-optimizing, without prespecified control model or variables setpoints, an object relative to a specific criterion or activity in response to variations on a prescribed number m of variables, comprising:

means for automatically planning a set of n statistically designed tests around a specified experimental point in a m -dimensional experimental region for testing the m variables in said n tests;
means for performing said n designed tests on said object;
means for determining from said n tests the combination of said m variables which optimizes said specific criterion or activity;
means for setting the conditions of said m variables at the thus-determined optimal combination before said combination significantly changes;

means for coupling the planning, performing, determining, and setting means for recycling to achieve self-optimizing control; and

during each self-optimizing cycle except for the first said planning means employing said optimal combination as the specified experimental point for the immediately following recycle.

2. A machine as in claim 1 wherein the object is a living being selected from the group consisting of human, animal, bacteria, and plant, the prescribed activity of the object relates to growth of the object, and the specific activity characteristics is the rate of growth.

3. A machine as in claim 2 wherein the prescribed activity relates to mental growth of the object, and the m variables are mental growth-affecting variables selected from the group consisting of equipment, materials, parts, procedures, and environment.

4. A machine as in claim 2 wherein the prescribed activity relates to physical growth of the object, and said m variables are physical growth-affecting variables.

5. A machine as in claim 1 wherein said determining means determines the optimal combination within several seconds.

6. A machine as in claim 1 including means for feeding back new knowledge bases for said planning means to replan, performing means to reperform, determining means to redetermine, and setting means means to reset.

7. A machine as in claim 6 wherein said planning, performing, determining, setting, and back-feeding means successively and cyclically operate according to the sequence given, and said back-feeding means substantially continuously feeds back information for substantially continuous, close-looped self-optimizing operation of the machine.

8. A machine as in claim 1 wherein said determining means generates machine intelligence including the optimal combination, and also including means for transferring such machine intelligence to a second object similar to said object.

9. A machine of claim 1 wherein said determining means comprises a computing means having a specified computing step time and the computing time for each self-optimizing cycle is no more than 1,792 times the computing step time.

10. A machine as in claim 1 wherein said m variables are continuous variables and wherein the machine is given an allowable range for each continuous variable but must operate at a time when no other knowledge bases are available, and wherein said automatic planning means plans, in the first self-optimizing cycle, the n statistically designed tests around the specified experimental point defined by the averages or midpoints of the allowable ranges for the m continuous variables.

11. A machine as in claim 1 of the type having errors due to misused or miscalibrated sensors, imperfect actuators, and drifting or partially damaged components, and wherein said setting means sets the conditions of said m variables at the apparent optimal combinations as determined by said determining means, with the machine still efficiently achieving true self-optimization because the errors are self-compensating in the operation of the machine.

12. A machine as in claim 1 wherein said planning means automatically plans the set of n statistically designed tests according to a fractional factorial design, with n being no more than one sixteenth ($4/16$) of the

test number required by the complete factorial design for the m variables.

13. A method for self-optimizing, without prespecified control model or variable setpoints, an object relative to a specific criterion or activity during the operation of said object and in response to variations on a prescribed number m of variables, comprising:

self-planning a set of n statistically designed tests around a specified experimental point in a m -dimensional experimental region for testing said m variables in said n tests;

performing said n tests on said very object in actual operation;

determining from said n tests the combination of said m variables which optimizes said specific criterion or activity during said actual operation;

setting the conditions of said m variables at the thus-determined optimal combination before said combination significantly changes;

repeating or recycling the self-planning, performing, determining, and setting steps according to the sequence given; and

during each self-optimizing cycle except for the first employing said optimal combination as the experimental point in the immediately following recycle.

14. A method as in claim 13 wherein said determining step determines said optimal combination within less than 1.79 milliseconds.

15. A method as in claim 13 wherein said determining step also generates machine intelligence including the optimal variables combination, and including transferring such machine intelligence to a second object similar to said object.

16. A method as in claim 13 wherein said self-planning performing, determining, setting, repeating or recycling, and employing steps are performed substantially continuously, cyclically and successively according to the sequence given.

17. A method as in claim 13 for self-optimizing with miscalibrated sensors and imperfect actuators including:

sensing with the miscalibrated sensors; continuously and automatically self-optimizing relative to the optimizing criteria by determining the apparent optimal variables combinations as sensed with the miscalibrated sensors; and

setting and resetting with the imperfect actuators at the thus-determined, apparent optimal variables combinations.

18. A method as in claim 17 for self-optimizing with statistically fluctuating, miscalibrated sensors and imperfect actuators wherein said continuous and automatic planning and executing steps comprise continuously and automatically planning and executing statistically designed experiments which are so balanced that in each experiment the effect of every control variable can be independently evaluated as if the entire experiment were performed just on this one variable with the other variables all kept constant; and

analyzing the test data to thus provide at least four-fold, virtual statistical replication to yield averaging effects thereby counteracting the effect of said statistical fluctuations.

19. A method as in claim 13 including the additional step of causing said self-planning, performing, determining, setting, repeating, and employing steps to parallelly and automatically perform, during each self-optimizing cycle, a plurality of the following tasks: 1. comprehensive and systematic R&D; 2. optimal manufacturing or

servicing designs; 3. 100% quality control; 4. procedure or equipment modifications; 5. materials and parts selections; 6. use of environmental changes for maximum benefits; 7. prototype or finished products manufacturing; and 8. generation of reliable and comprehensive knowledge bases.

20. A method as in claim 13 wherein said self-planning step automatically plans the set of n statistically designed tests according to a fractional factorial design, with n being no more than one sixteenth ($1/16$) of the test number required by the complete factorial design for the m variables.

21. A method for self-optimizing, without prespecified control model or variables setpoints, a computer software relative to a specific criterion in response to variations on a prescribed number m of software-related variables, comprising:

self-planning a set of n statistically designed tests around a specified experimental point in a m -dimensional experimental region for testing the m variables in said n tests;

performing said n designed tests on said software; determining from said n tests the combination of said m variables which optimizes said specific criterion;

setting the conditions of said m variables at the thus-determined optimal combination before said combination significantly changes;

repeating or recycling the self-planning, performing, determining, and setting steps in the order given; and

during each self-optimizing cycle except for the first employing said optimal combination as the specified experimental point in the immediately following recycle.

22. A method as in claim 21 wherein said self-planning step automatically plans the n designed tests according to a fractional factorial design, with n being no more than one sixteenth ($1/16$) of the test number required by the complete factorial design for the m variables.

23. A method as in claim 21 for self-optimizing a computer software in terms of its generation, modification, or usage; and wherein the optimizing criterion is selected from the group consisting of productivity, product or service cost, profit, accuracy, and reliability; and including selecting the m variables from the group consisting of procedures, equipment, and software parts.

24. A method as in claim 23 including selecting the procedural variables from the group consisting of uses of different physical/chemical models, mathematical equations and formulas, and numerical computation/analysis techniques.

25. A method as in claim 21 including choosing the procedural and software variables from the group consisting of finite element grid shapes and sizes; the locations, sizes, starting and finishing points, and step sizes of the do loops; and the number, locations, types, contents, and characteristics of subroutines.

26. A method as in claim 21 including choosing the m variables at least partly from equipment variables selected from the group consisting of the number, types, locations, and operational characteristics of the different processors and coprocessors, monitors, disk or tape drives, telecommunicating systems, modems, and printers.

27. A method as in claim 21 for application of the software in self-optimizing computer simulation, design,

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engineering, and training; signal processing; image processing; sensor data fusion; battle management; geopolitical assessment; financial data analyses; and stock, option, and commodity trading; and including choosing the m variables at least partly from software-related variables.

28. A method as in claim 21 wherein the m variables are continuous variables and only an allowable range for each continuous variable is given for use at a time when no other knowledge bases are available, and wherein said self-planning step plans, in the first self-optimizing cycle, the n statistically designed tests around the specified experimental point defined by the averages or midpoints of the allowable ranges for the m continuous variables.

29. A method of self-optimizing relative to a prespecified optimizing criterion with a group of m preselected control variables, comprising:

automatically planning and executing a statistically designed R&D experiment on said m variables;
determining from said experiment the optimal variables combination;

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setting said m variables at the thus-determined optimal combination;

repeating the planning and executing, determining, and setting steps according to the sequence given; and

feeding back in any given R&D experiment except for the first information at least from the immediately preceding experiment.

30. A method as in claim 29 including:

generating relevant, timely, and new knowledge base in the first designed experiment;

using the newly generated knowledge base in the setting of the variables;

regenerating in subsequent designed experiments still newer and more updated and accurate or refined knowledge bases; and

replacing the old knowledge bases with the newest knowledge base for uses in the resetting of the variables.

31. A method as in claim 30 for self-optimizing with a drifting equipment having a specified drift cycle time and including the additional step of controlling the cycle time for repeating the designed experiment to less than one half of the drift cycle time.

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